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Wavelet De-noising of Hyperspectral Data

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Abstract

This paper presents a method for noise removal from hyperspectral data using wavelets. Normally, data collected in the field will contain several types of noise. One type is the small amount of noise that is superimposed along the signal. This noise will not degrade the characteristic shape of the signal, but will add a small systematic disturbance to it. This noise is usually caused by the physical instrument or field environment conditions. This noise, although small, can be troublesome in interpolating data. The natural growth in the understanding of wavelet applications now affords the capability to remove this noise without degrading the signal. A wavelet transform was applied to hyperspectral percent reflectance - wavelength data sets. The resulting power spectrum was filtered so that specific wavelet coefficients were removed. An inverse wavelet transform was then applied to this filtered spectrum to obtain a noise free data set.

Key words: Hyperspectral, noise removal, wavelets.

Introduction

Hyperspectral data, at 5 - 10 ηmeter bandwidth, has been used to conduct basic field and laboratory research to determine relations between earth surface components, targets, background characteristics, influencing climatic and meteorological conditions, and their patterned or spectral reflectance, luminance, and emittance values as recorded by airborne or satellite remote sensing systems. A number of products have been developed from these measurements including databases, empirical and mathematical models, manual and digital image analysis paradigms, and specialized detection techniques for U.S. Army terrain information requirements, intelligence needs, targeting, and environmental applications. Research and exploratory development also has been conducted to identify new technologies and pursue new initiatives using hyperspectral remote sensing measurements together with interferometric synthetic aperture radar (IFSAR) information to enhance the Army's effectiveness in carrying out its land combat mission.

This effort was motivated by the desire to accurately interpolate hyperspectral reflectance measurements to one (1) ηmeter from two (2) and five (5) ηmeter field-collected data and to determine radiance or reflectance values at specific wavelengths. Before this can be achieved, noise in the data must be removed with the lowest probability that sharp signal features will become blurred, and spikes, jumps, and other non-smooth features will be unaffected. The natural growth in the understanding of wavelet applications now affords the capability to remove this noise without degrading the signal. Furthermore, ridding signals of noise often is much easier in the wavelet domain than in the original domain.

De-noising Procedure

The de-noising procedure involves only three basic steps. First, the wavelet transform of the signal is taken; second, the wavelet coefficients in the transform are filtered in such a way that only those coefficients that correspond to the noise are removed from the wavelet transformed signal. The third step is to do an inverse wavelet transform to reconstruct the original signal, but without the noise. A fundamental understanding of the signal

characteristics is needed in advance of de-noising. It also should be understood that it is almost impossible to filter noise without affecting the signal [Strang & Nguyen 1996].

There are many different wavelets, and new ones are constantly being invented and developed. Before any noise removal takes place, the type of wavelet must be designed or selected from many that are available. This selection process can be complex involving the data type, time, and efficiency, among other factors. For hyperspectral data, as will be shown later, a number of wavelets do a very good job of noise removal.

The filtering of the coefficients works by selecting a threshold value and setting those wavelet coefficients that are below this value to zero (0). It could be argued that determining the threshold value is arbitrary or difficult, but much work has been done by others [Bruce et al, 1996] so that now there is little mystery about this value.

Data

The data used in this effort was collected over the Yuma, Arizona desert during the months of July and August 1996 using a Geophysical Environmental Research Spectrometer. Table 1 shows a small sample of a data set of raw data collected. This particular target is a smooth plywood board. The percent reflectance was measured at wavelengths (λ) of 300 to 1000 ηmeters at regular two (2) ηmeter intervals. Figure 1 displays a plot of this data. The plot shows a small sine-wave-like disturbance along the signal. It is this disturbance that should be removed. These raw data were interpolated to one (1) ηmeter using a simple cubic spline. Table 2 shows the interpolated values. Note that these interpolated values are computed before any noise reduction routine is applied to the data.

A noise removal routine was applied to the raw data. The routine employs a Daubechies-4 wavelet. Figure 2 shows a plot of the data after noise has been removed. These noise-free data were interpolated to one (1) ηmeter using the same cubic spline as before. Table 3 shows these interpolated values. The difference in the before and after noise removal interpolated values is not dramatic, but as can be seen from the comparison of the two plots, the sine-wave-like disturbance has been removed. Much resolution is lost in the reformatting of the plots, but the real-time plots clearly show the disturbance removed. Both plots were generated without the interpolated values. The largest difference between the raw and de-noised measured values is approximately ± 0.5 percent reflectance, and approximately ± 1.0 percent in the interpolated values. The significance and justification for the removal of such small amounts of noise is beyond the scope of this paper.

Table 1. Sample of Hyperspectral Data
Smooth Plywood

λ ηmeters	Percent Reflect.	λ ηmeters	Percent Reflect.
602	27.8407	620	29.6886
604	27.9367	622	30.0029
606	27.9490	624	30.1785
608	28.0247	626	30.2789
610	28.2890	628	30.3514
612	28.6015	630	30.4349
614	28.8452	632	30.4219
616	29.0494	634	30.2204
618	29.3175	636	29.9513

Table 2. Sample of Hyperspectral Interpolated Data
Smooth Plywood

λ ηmeters	Percent Reflect.	λ ηmeters	Percent Reflect.
601	27.7440	619	29.4984
603	27.9049	621	29.8616
605	27.9456	623	30.1052
607	27.9671	625	30.2349
609	28.1386	627	30.3144
611	28.4490	629	30.3960
613	28.7348	631	30.4497
615	28.9482	633	30.3399
617	29.1688	635	30.0854

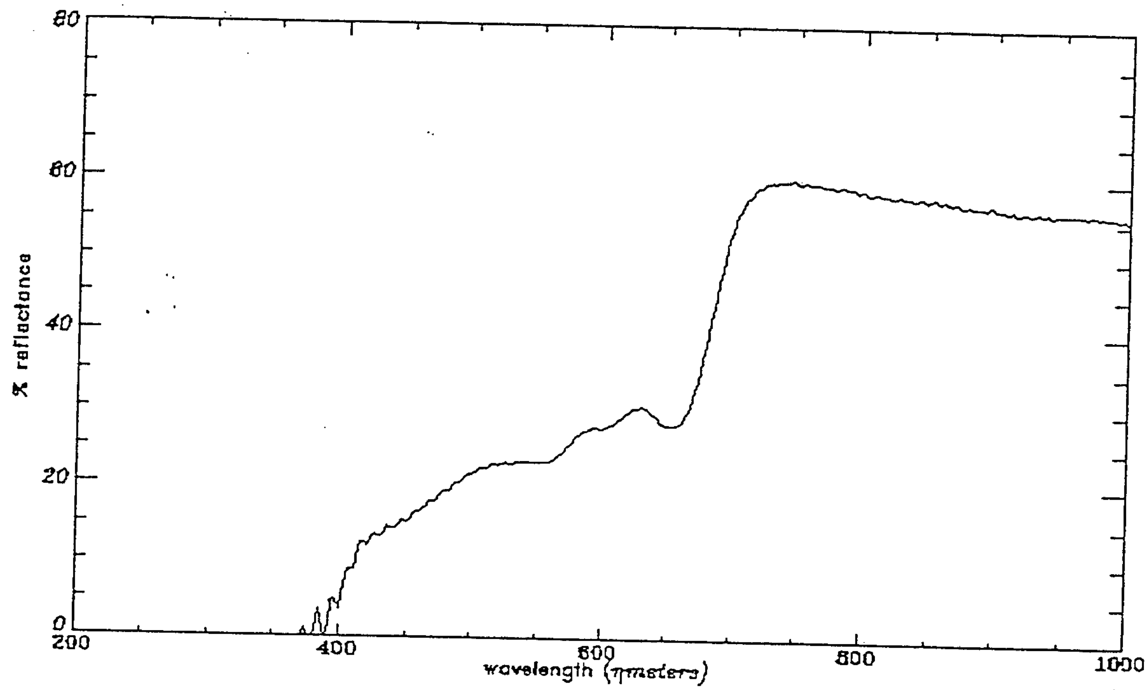

Figure 1. Raw Data (Smooth Plywood)

Table 3. Sample of Hyperspectral De-noised Interpolated Data
Smooth Plywood

λ ηmeters	Percent Reflect.	λ ηmeters	Percent Reflect.
602	28.0107	620	29.6241
603	28.0822	621	29.7232
604	28.1539	622	29.8181
605	28.2353	623	29.9128
606	28.3227	624	30.0069
607	28.4105	625	30.1016
608	28.4951	626	30.2067
609	28.5740	627	30.3230
610	28.6477	628	30.4065
611	28.7187	629	30.4119
612	28.7962	630	30.3639
613	28.8890	631	30.2917
614	28.9918	632	30.2193
615	29.0982	633	30.1571
616	29.2036	634	30.0852
617	28.3057	635	29.9848
618	29.4090	636	29.8822
619	29.5172	637	29.8046

Noise-Added Data

To better assess wavelet de-noising, a slightly different procedure was implemented with a different data set.

This second data set is the hyperspectral measurement of a camouflage net. A small amount of noise was added to the data to ascertain that the data are not noise free. Table 4 shows a small sample of these raw measurements. Note that these values are irregularly spaced and this data has to be resampled to regularly spaced values. The wavelet transform assumes evenly spaced data, however this data set is very close to being evenly spaced with not much error introduced. The spacing for these data are 1.62 ±0.01 ηmeters. It should be understood that the spectrometer has a tolerance range in the collection of data. The data are recorded as being evenly spaced, however there is a very small variation in the measurement interval. Table 5 shows the resampled measurements with noise added.

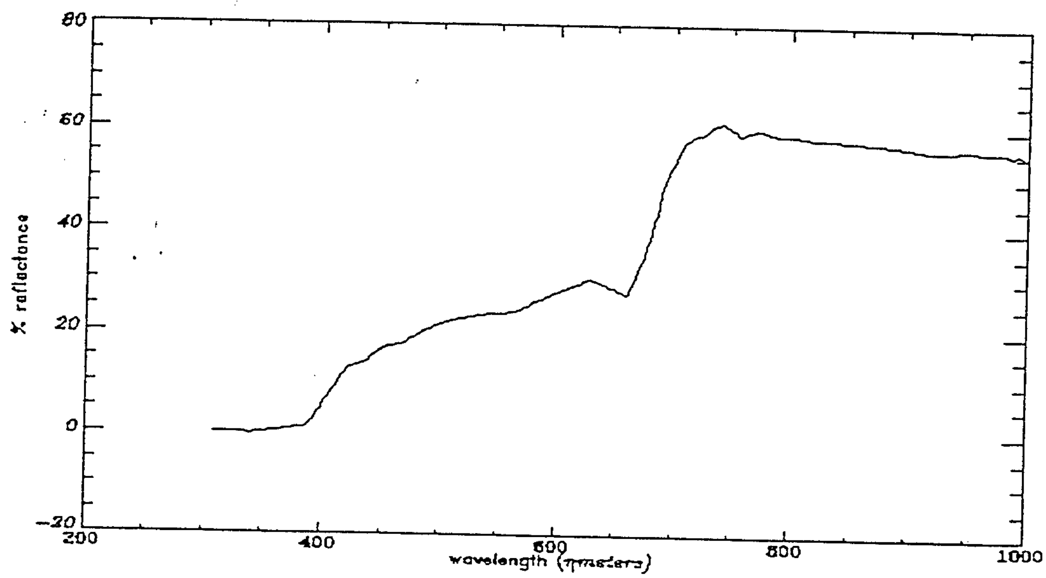

Figure 2. De-noised Data (Smooth Plywood)

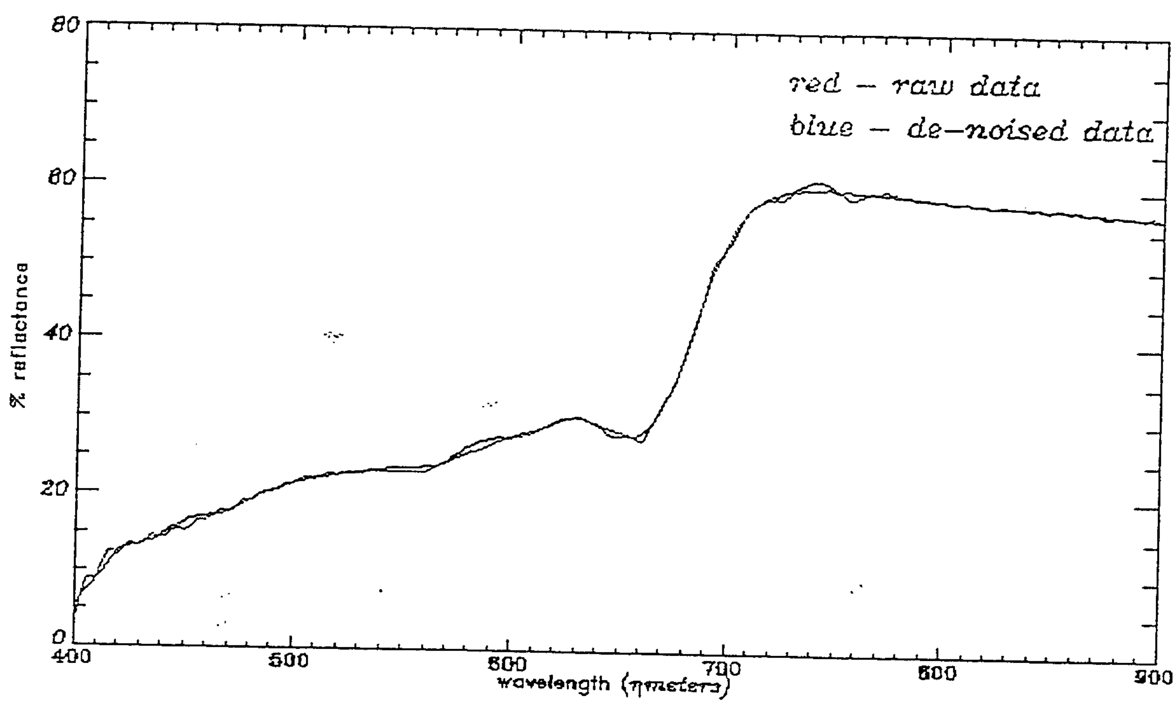

Figure 3. Raw & De-noised Data Plots (Camouflage Net)

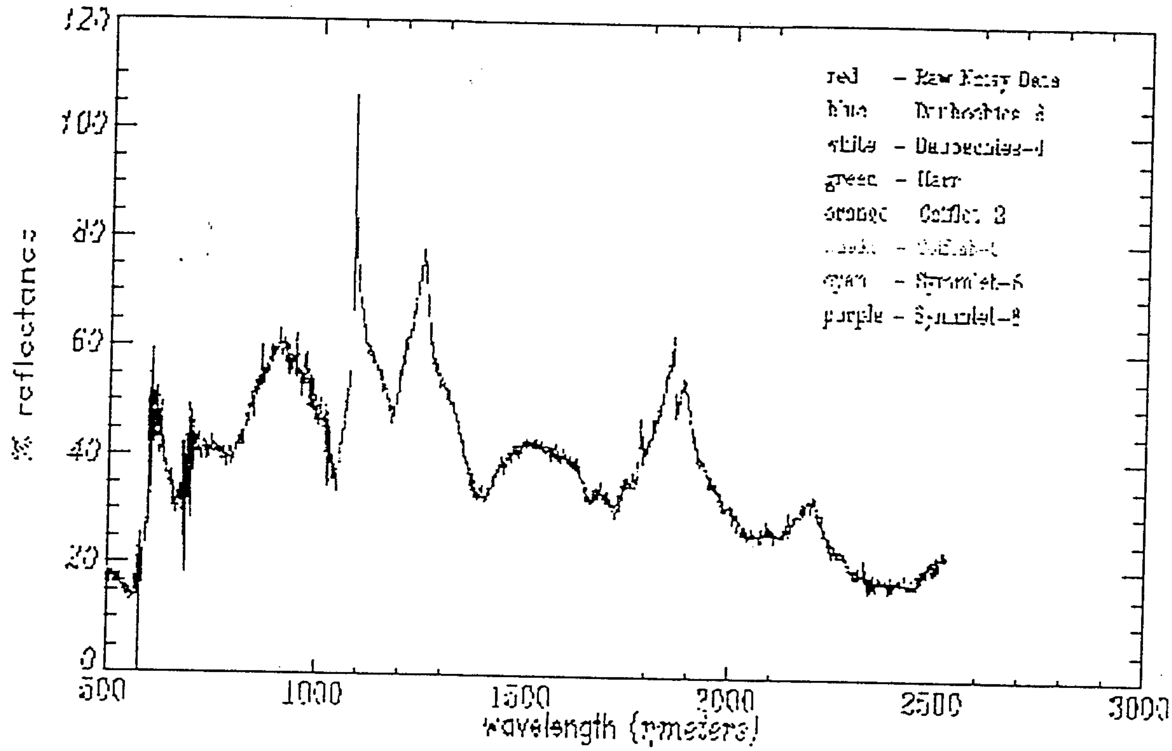

Figure 4. All Wavelets Plot (Smooth Plywood)

The noise removal routine was applied to this resampled data. Figure 3 is a plot of the raw data and the noise-added data. The raw data were de-noised and then resampled to regularly spaced values. The difference in the values between de-noising first and then resampling, and resampling and then de-noising is very small, which is an indication that the irregular sampled data are close enough in the interval range to be treated as evenly sampled data.

This data set was de-noised using the same Daubechies-4 wavelet routine. It also was de-noised with Daubechies-6, Symmlet-6, Symmlet-8, Coifiet-2, Coifiet-3, and Haar wavelet routines. Figure 4 is a composite plot of all these data. All plots are within two (2) percent reflectance of each other, which indicates that all of these wavelets do the same job for de-noising hyperspectral data. The only one plot that seems out of place is the Haar wavelet transform. The Haar wavelet produces a step function that was expected because of the very nature of the Haar wavelet. Of the seven wavelets used in this effort, Symmlet-8 appears to do a better job. The rationale for this statement is that when relatively noise-free raw data were plotted and noise was added to these data, and then the noise-added data were de-noised using the different wavelets, the resulting Symmlet-8 data were closer to the original data than the other wavelets. This procedure was performed only a few times therefore the results may not be conclusive. More analysis is needed.

Table 4. Sample of Raw Hyperspectral Data

Camouflage Net

λ ηmeters	Percent Reflect.	λ ηmeters	Percent Reflect.
600.0700	38.3051	619.6100	47.3398
601.7100	40.4237	621.2400	46.2093
603.3400	42.2557	622.8600	45.8673
604.9700	44.5182	624.4800	45.5640
606.6000	45.7048	626.0900	44.4367
608.2300	46.2652	627.7100	43.6922
609.8600	46.6673	629.3300	43.3294
611.4900	47.0456	630.9400	42.1288
613.1200	47.3857	632.5600	40.7885
614.7400	46.6979	634.1700	39.1311
616.3700	46.8673	635.7800	38.1360
617.9900	46.8724	637.3900	37.4394

Table 5. Sample of Interpolated Data

Camouflage Net

λ ηmeters	Percent Reflect.	λ ηmeters	Percent Reflect.
600	38.3750	612	43.4063
601	58.3281	613	49.4063
602	33.5625	614	51.7500
603	40.7422	615	46.1563
604	42.4688	616	48.9688
605	51.9688	617	47.1563
606	44.0313	618	49.4414
607	46.7500	619	46.3750
608	48.6875	620	41.0625
609	48.0000	621	49.3750
610	40.9688	622	44.5000
611	50.2813	623	55.0000

Conclusions

After analysis of the results it is concluded that wavelets are a viable tool for noise removal from hyperspectral data. There is no substitute for a good measurement, however the times when data has to be interpolated or resampled, wavelets seem to provide a good solution. Many commercial software packages now include wavelet tools that make it easy to work with wavelets.

References

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